Ensemble U-Net for 2019 Kidney Tumor Segmentation Challenge

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Abstract. Its known to us all that convolutional network makes medical processing more accurate and efficient as a significant tool for assisting doctors. In deed,aiming at kidney and diversity of kidney tumor,there already have various effective segmentation results from networks learning, and they are more comparable. Therefore,methods based on networks has become a mainstream in image processing.For this MICCAI kidney and kidney tumor segmentation challenges, we proposed our own scheme.We are inspired by U-Net,experiment in five U-Net on 300 abdominal CT scan of arterial phase in patients with renal cell carcinoma, then take all results as an ensemble and use it as the final result.

Keywords: kidney tumor · segmentation · U-Net and esemble.

1 Introduction

The kidney is located on both sides of the spine, close to the posterior wall of the abdomen, behind the peritoneum.But kidney tumors are in different sizes and not easy to recognition,which directly leads to difficulty in tumor segmentation. Its well known to us all that traditional methods based on manual are too expansive and time-consuming,and different doctors have disagreement in hand-crafted features. So this type of methods is not generalized and then methods about learning come into being. To consider CNN as the representative for neural networks are in full swing in computer vision field,mainly used for classification,segmentation,tracking and other tasks. The segmentation-based networks generally implements end-to-end classification based on the voxel-wise characteristics of the image. The chief obstacles of medical pictures processing here also have difficulties are vague image, more noisy points and uneven grayscale. Figure 1 shows kidney and tumor have low contrast,unclear boundary,extremely small tumor and so on.

2 Related Work

In recent years,some traditional network-based methods for kidney and tumor segmentation truely achieve good results,but there also exsits a little dificiency,like too high time cost and many manual work.More and more data experiments show that segmentation based on learning methods hold a large more

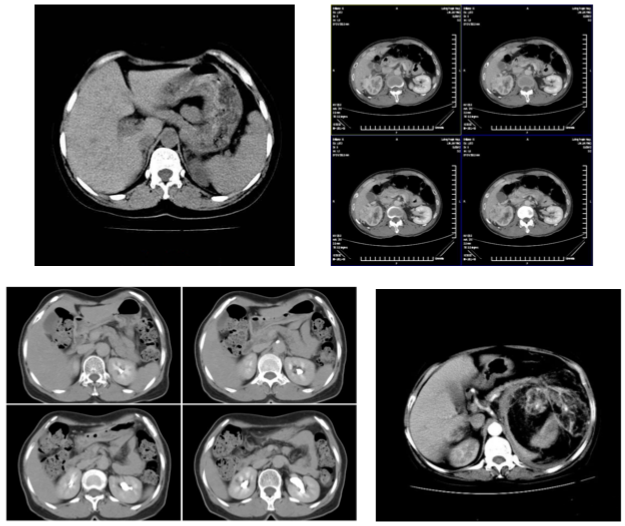

Fig. 1. kidney and kidney tumor.

advantages,which indicates that deep learning growly takes the lead in computer vision.

3 Our Method

3.1 Network Architecture

This design is inspired by U-Net,which was initially used to separate from cell membrane,and also have acquired ideal results on other organs segmentation. U-Net mainly contains two symmetrical sampling stages,namely contracting path(also called encoding stage) to capture context information and expanding path(or decoding stage) that enables precise localization. And the remarkable superiority of this U-type structure lies in repeated up-down sampling to extract low and high level picture features. Besides,U-Net is suitable for small data set,that handle with the key problem of lacking of medical image data.
Now,we make improvements on the foundation of U-Net according to kidney and its tumor traits,that is to random initially train five times,and make esemble with averaging all results.We choose to ensemble principally due to three aspects.First,ensemble can integrate multiple models to avoid segmentation mistakenly due to single model deviation. In the second place,previous studies have shown ensemble can significantly improve experiment performance.

3.2 Implementation

Our proposed method is implemented using NVIDIA Titan XP,and we start our training with Adam optimizer,initial learning rate is 3×10^{-4}.Probably 250 training batches are as an epoch.Of course,training data on this challenge is limited,we also choose proper data augmentation methods like mirroring, elastic transformating randomly and rotating randomly.With different techniques,overfitting can be avoided.

3.3 Results

Our experiment results is submitted as predictions.zip,including kidney and tumor segmentation of 90 patients by our ensemble version of U-Net.Our experiment results are more idel intuitively.we use Dice and Cross-Entropy as loss function of this experiment.

4 Conclusions

In this 2019 Kidney Tumor Segmentation Challenge,we proposed our own segmentation technique,namely training U-Net 3 times.Furthermore,we make an esemble with all results and find the performance of ensemble better and have higher accuracy.we are looking forworad that if more training times with U-Net can be united more ideal results.But one key point is time cost and computation complexity.

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